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Repetitive Control to Improve Users' Thermal Comfort and Energy Efficiency in Buildings

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Abstract: The development of control systems to reach and maintain optimal thermal comfort inside buildings is a research topic which has received great attention in the last several years because people's productivity is linked to their comfort. The main weakness of these control systems is that they do not take into account that people affect their own thermal comfort, since humans are heat sources that increase the temperature inside buildings. For this reason, people can be considered as disturbances to thermal comfort control systems. Usually, people follow a timetable along the week, so they enter and leave buildings at the same time every day. Taking this behavior into account can be very useful in improving people's thermal comfort. In this paper, a repetitive control (RC) approach that makes use of this information to anticipate the effects of people on indoor temperature is presented. Besides that, the control system includes a proportional–integral (PI) controller in charge of counteracting the non-periodic disturbances. Simulation results obtained with this control system through a room simulator are presented in order to show its efficiency.

Keywords: repetitive control; thermal comfort; Predicted Mean Vote (PMV) index; energy efficiency

1. Introduction

In developed countries, almost 40% of the energy is utilized in buildings. HVAC (Heating, Ventilation and Air Conditioning) systems use more than half of this amount [1–3]. Moreover, buildings must comply with indoor environmental quality (IEQ) standards [4–8]. Therefore, different strategies to maintain thermal comfort in edifices have been extensively investigated in research in the last several years (i) to provide appropriate living conditions, since thermal comfort impacts people's productive capacity [9–13], and (ii) to enhance energy efficiency [14–16].

1.1. Past Studies

Thus, an extensive variety of control approaches for HVAC systems has been tried and tested in an attempt to improve people's thermal comfort sensation inside buildings. It is necessary to emphasize the use of model-based predictive control (MPC) as one of the most widespread approaches for this purpose in view of the fact that it can predict the future states of controlled systems through the use of a system model, disturbances, and noise [17]. Some recent examples where MPC or any of its variations is used can be found in [18–20].

In [18], an MPC is proposed. Aiming to achieve better predictions, such a controller is based on a linear time-dependent (LTD) model. Linear time-invariant (LTI) models are usually used. It is important to mention that the use of an LTD model does not increase the execution time associated with the optimization problem, since the objective function remains convex. The proposed linear MPC was compared with a non-linear MPC in terms of efficiency and effectiveness. Results showed that the linear MPC outperforms the non-linear MPC. It obtains a good equilibrium between the quality of the solution and the required computing time. In [19], a bi-objective problem is considered. Specifically, the operating costs derived from raising room temperatures and thermal comfort, estimated through the Predicted Percentage of Dissatisfied (PPD) index, are optimized simultaneously. To do this, the EnergyPlus software and an optimization engine, based on MATLAB (2010b, MathWorks, Natick, MA, USA), were combined. It is worth mentioning that, as the authors consider the PPD index instead of the Predicted Mean Vote (PMV), they did not take into account signs of thermal sensation. Finally, in [20], an economic MPC algorithm that allows one to optimize both energy cost and energy demand using the time-of-use price policy is presented. The control architecture was developed through the Internet in order to carry out the tests at a remote location; specifically, the proposed controller is checked in a remote commercial office building. Other control techniques widely used for thermal comfort include artificial neural networks [21–23], genetic algorithm control techniques [24,25], fuzzy logic control techniques [23,26,27], and controllers based on PMV evaluation [14,16].

1.2. Novelty of This Work

The majority of these works take into consideration numerous disturbances (outdoor air temperature, radiant temperatures, the use of electric appliances, weather conditions, etc.). These disturbances can influence indoor temperature and, as a consequence, users' thermal comfort. These studies have employed simulation tools to test developed control systems, but these simulation tools have only provided surface temperatures and not the mean radiant temperature, so the PMV index has not been correctly calculated. Only a small number of papers consider a variable that, in some surroundings, might interfere with people's thermal comfort sensations: the people themselves. Specifically, in those buildings or dwellings with a high user ratio per square meter, the principal factor that has a considerable impact on indoor air temperature is the people themselves, since they are heat sources. People add heat to their surrounding environment through their quotidian activities, which entails an increase in indoor air temperature. Furthermore, there are diverse environments such as schools, offices, and labs where users' entries and departures are characterized by a periodic pattern, so it is plausible to predict and react accordingly to indoor air temperature response.

Therefore, this paper presents a repetitive control (RC) approach to neutralize people's influence on thermal comfort sensation and thus to enhance energy saving. RC [28,29] is a technique based on the internal model principle [30] and is able to track or reject periodic signals of well-known frequency. The fundamentals of RC is that a certain system which performs a certain activity several times can increase its performance from preceding repetitions (executions). Only a small number of papers consider this periodic behavior so as to prevent its impact on thermal comfort [31,32]; in other works, the RC is used to counteract periodic effects of the weather [33,34]. The control approach proposed in this paper has been tested by means of simulation tests, employing a room simulator which makes use of a non-linear model based on first principles [35]. Hence, the benefits of introducing an RC in the control system is shown via comparisons with other control systems.

1.3. Structure of the Work

The rest of the work is composed by five additional sections: Section 2 deals with methodology used in this work. This methodology includes: (i) the most usual index to estimate thermal comfort: the PMV index; (ii) the proposed control system which takes into consideration the influence of people on their own thermal comfort; (iii) the simulation tool used to evaluate the goodness of the presented control system and; (iv) the linear model and the person profile to tune the controller. The simulation results are widely discussed in Section 3 and, finally, in Section 4, the main conclusions are summarized.

2. Methodology

In this section the methodology followed in this work is described. Firstly, the index used to estimated the thermal comfort is defined. Secondly, the proposed controller to counteract the effects of people on their thermal comfort is described. Later, the test bed model in which the proposed controller is tested is explained. Finally, the linear model and the person profile used to tune the controller is shown.

2.1. Thermal Comfort and the PMV Index

In general, comfort sensation can be contemplated as a cognitive process affected by diverse sorts of processes, with physiological, physical, as well as psychological aspects [36]. Furthermore, standards such as ASHRAE 55 [37] and ISO 7730 [38] define thermal comfort as "that condition of mind which expresses satisfaction with the thermal environment." This definition was firstly formulated in the 1970s by [39,40]. Additionally, it relies on disparate circumstances such as the surrounding environment, the time of year (summer, winter, etc.), the location of the person, why she/he is there, etc. However, in accordance with international standards such as [8,38], although the living environment and habits differ in many countries, the indoor air temperature in mechanically conditioned buildings is similar worldwide.

Therefore, it is possible to find in the literature several indexes which provide an appropriate mechanism to determine thermal comfort conditions within a particular environment. Nevertheless, one of the most widespread indexes suitable for mechanically conditioned buildings is the (PMV). It reflects the mean of a sizeable set of people with respect to their thermal sensation when they are exposed to specific environmental conditions for a considerable amount of time [37–39]. The values obtained through the PMV index can be classified by a thermal sensation scale, where 0 is neutral, ± 1 is slightly warm/cool, ± 2 is warm/cool, ± 3 is hot/cold. Furthermore, according to the international standard ISO 7730 [38], to guarantee a thermal comfort situation of class A, it is necessary to achieve a PMV index value equal to 0 with a tolerance of ± 0.2. This index is calculated as a function of the energy balance of the human body, conceiving the body as an indivisible entity. Hence, the PMV index can be obtained based on six variables:

$$PMV = f\left(M, I_{cl}, t_a, RH, t_r, v_{ar}\right) \tag{1}$$

where variables are defined as follows:

- M: metabolic rate $(\mathrm{W/m^2})$.
- I_{cl}: basic clothing insulation $((\mathrm{m^2\,K})/\mathrm{W})$.
- t_a: indoor air temperature $(^{\circ}\mathrm{C})$.
- RH: relative humidity $(\%)$.
- t_r: mean radiant temperature $(^{\circ}\mathrm{C})$.
- v_{ar}: relative air velocity $(\mathrm{m/s})$.

Nevertheless, as it is widely analyzed in [41,42], the methodology which should be followed in order to estimate the PMV index is not trivial, and many mistakes can be made. More in detail, half of these variables, that is, indoor air temperature, relative humidity, and air velocity, can be measured directly with sensors. Furthermore, the mean radiant temperature can be estimated (i) from the plane radiant temperatures in six opposite directions or (ii) from a black globe thermometer [43,44]. However, to acquire these variables correctly, the sensors must have certain characteristics, and a particular methodology must be followed [45]. Finally, both the metabolic rate and clothing insulation variables cannot be measured in a straightforward way, since they depend on the users at each time instant.

Hence, the appropriate value for both variables is tabulated in manuals and standards [37,38]. A detailed explanation about the procedure used to determine PMV can be found in [37–39].

2.2. The Control System

The internal model principle [30] establishes that in order to follow references and reject disturbances without a steady-state error, it is necessary to include its internal model in the controller. Figure 1 shows the traditional block scheme used to represent the most relevant internal models. As can be seen, it is composed of the positive feedback connection of a system formed by the series connection of $H(z)$ and $\sigma W(z)$ and a unitary gain, yielding to

$$I(z) = \frac{\sigma W(z)H(z)}{1 - \sigma W(z)H(z)}. \quad (2)$$

Using $\sigma \in \{-1, 1\}$ and $W(z)$, specific periodical signal internal models can be defined [46]. For $\sigma = 1$ and $H(z) = z^{-N}$, the generic N-periodic internal model is obtained.

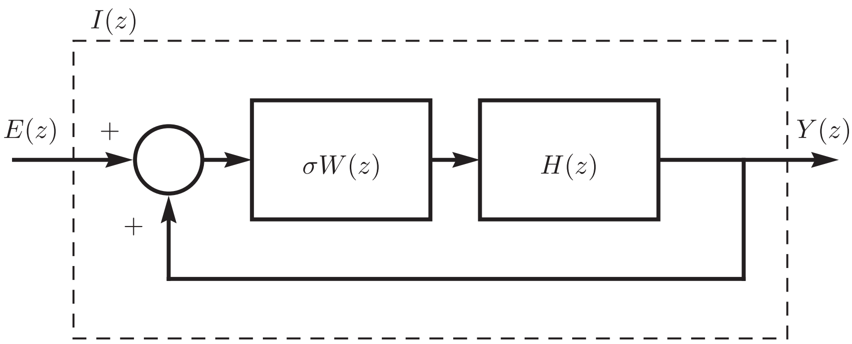

Figure 1. Periodic signal generator block scheme. $\sigma \in \{-1, 1\}$ and $W(z)$ are used to define the particularities of the signal. $H(z)$ is a low-pas filter used to introduce robustness in the closed-loop system.

Internal models are either marginally stable or unstable [47]; therefore, to assure closed-loop stability, it is required they be combined with other components. The literature provides different ways of addressing this issue [47]. By far, the most popular scheme is the plug-in [46,48] approach, which is shown in Figure 2. Besides the internal model, this scheme contains the plant to be controlled, $G_p(z)$, an inner controller, $G_c(z)$, which is used to provide robustness against uncertainty, and a stabilizing controller, $G_x(z)$. The closed-loop stability can be guaranteed by fixing $G_c(z)$ such that $T_o(z) = G_c(z) G_p(z) / \left(1 + G_c(z) G_p(z)\right)$ is stable, and choosing $G_x(z) = k_r (T_o(z))^{-1}$ [46,48]. In this formulation, two tuning parameters exist: k_r, which it used to define the settling time, and $H(z)$, which is usually a null-phase low-pass filter with a maximum gain of 1 and a cut-off frequency selected taking into account the model uncertainty.

Although RC offers excellent performance for N-periodic signals, it might degrade its efficiency for other type of signals. To illustrate this, let us here introduce the sensitivity transfer function, which relates the error, $E(z)$, with the reference $R(z)$ (Figure 2):

$$\frac{E(z)}{R(z)} = S_o(z) S_{Mod}(z)$$

where $S_o(z) = \frac{1}{1+G_c(z)G_p(z)}$ is the sensitivity function without the RC, and

$$S_{Mod}(z) = \frac{1 - \sigma W(z)H(z)}{1 - \sigma W(z)H(z)\,(1 - k_r)}.$$

Figure 3 shows the magnitude of frequency response of $S_{Mod}(z)$ for $H(z) = 1$, $W(z) = z^{-N}$ and $\sigma = 1$, which corresponds to the ideal case (no uncertainty in the model) and different values of k_r. As can be seen, it is zero for dc frequency, the N-periodic signal frequency, $\frac{2\pi}{N}$, and all of its harmonics. This guarantees that the error will be zero in steady-state for signals containing these frequency components. Differently, those frequencies in between the gain increases, meaning that those frequencies will be amplified (the error might be large). As can be seen in Figure 3, the inter-harmonic amplification depends on the value of k_r. This parameter is directly related with the closed-loop system settling time, the higher values of k_r related to the faster convergence. Due to this, it must be selected, making a trade-off between the desired settling and the allowed inter-harmonic amplification.

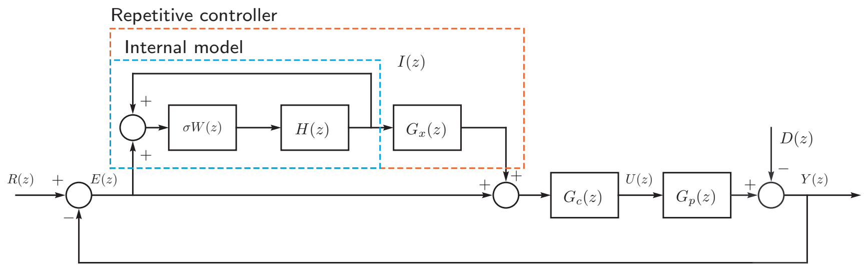

Figure 2. Repetitive controller plug-in block-diagram.

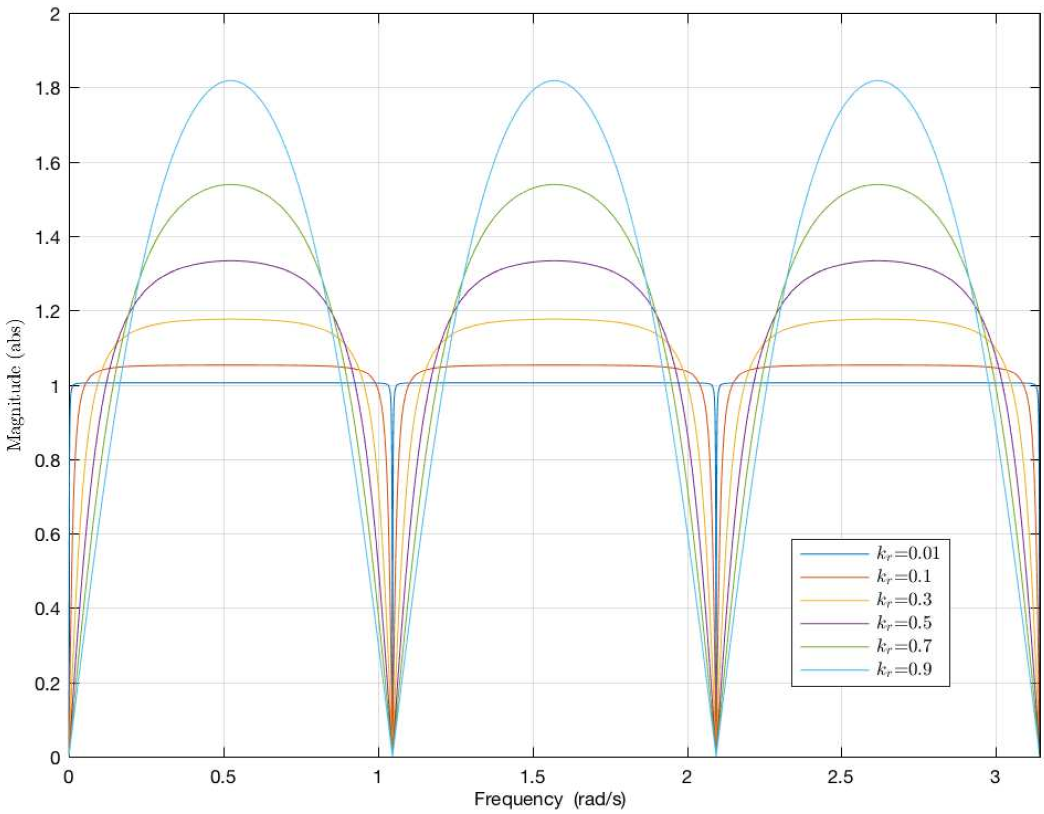

Figure 3. Magnitude of the frequency response of $S_{Mod}(z)$, for $\sigma = 1$, $H(z) = 1$, $W(z) = z^{-N}$ (N = 6), and different values of k_r.

2.3. Test Bed Model

2.3.1. CIESOL Building

This work presents a control system to guarantee an adequate thermal comfort sensation inside a certain environment. This control architecture includes an RC, which takes into account people's influence on their own thermal comfort sensation. This control system has been evaluated by simulation tests into a representative enclosure of a bioclimatic building in order to assess its fulfilment, specifically, the CIESOL building (http://www.ciesol.es), see Figure 4, which is a research centre devoted to solar energy and belongs to the grounds of the University of Almería (Spain).

Figure 4. Main entrance to the CIESOL bioclimatic edifice.

The CIESOL building is distinguished by a total floor area of 1072 m^2 distributed in two floors. It contains several bioclimatic mechanisms (shading element of the roof, HVAC based on solar energy, a photovoltaic field, and so on) since it has been built to be a nearly-zero-energy building (NZEB). Thus, the HVAC with two operation modes (summer or winter) generates heat or chilled air for the entire dwelling based on the users' demand. To do that, several water pipes, through which chilled or hot water flows, are distributed throughout the CIESOL building and, at each enclosure, there is a fan-coil unit that introduces air at a desired temperature by managing the volume of the air that is inserted into the room and the amount of water that flows through the fan-coil [17].

On the other hand, the CIESOL dwelling operates as a research centre which studies bioclimatic strategies and how they affect energy consumption and greenhouse effect gas production. The building has a considerable network of actuators and sensors, as is shown in Figure 5, which have been installed to accomplish the specifications provided by the international standard ISO 7726 [45]. Five characteristic rooms have been chosen, and different types of actuators and sensors placed within them. They are equipped with air, plane-radiant and globe temperature sensors, relative humidity sensors, an occupancy rate system, and, as main actuators, automatized windows and blinds, and a fan-coil unit. Moreover, at the building roof, a weather station composed of a variety of sensors (sensors measuring relative humidity, radiance, temperature, luminance, air velocity, etc.) is also included in the building. Additionally, the amount of people inside each room is measured through an occupancy rate system, see Figure 5, which is formed by photovoltaic sensors that allows one to determine how many people enter or leave the room.

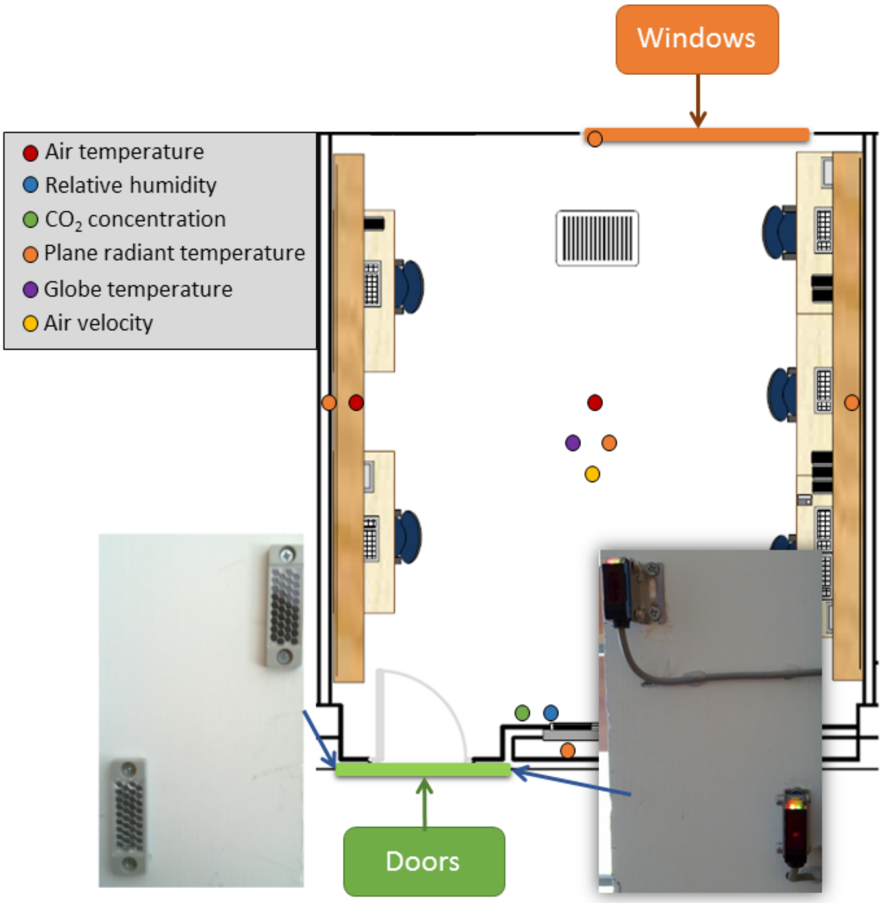

Figure 5. Detailed scheme of the main sensors and the occupancy rate system installed at the selected room in accordance with standard ISO 7726 [45].

To perform the simulation tests in order to check the proposed control system, one room was chosen principally due to its occupancy outline. The selected room, which is a laboratory, is situated on the first floor and is oriented northward. Furthermore, it has a window with a total surface of 2.15×2.09 m^2 and a total volume of 76.8 m^3. In addition, it has a fan-coil unit which is used to manage users' thermal comfort. Thus, the development of an appropriate model that precisely captures indoor dynamic behavior, i.e., able to act as a simulator, is necessary. A fundamental principles model has been obtained. An explanation of this model is provided in Section 2.3.2.

2.3.2. Room Simulator

In this work, the room simulator shown in [35] was used. To develop this simulator, a room was contemplated as a complicated system consisting of diverse types of components, such as, actuators, windows, and walls. In addition, it is important that certain factors such as the outside characteristic weather and the environmental conditions in the surrounding rooms are considered. Thus, the existing relations among the previously mentioned elements through mass transfer and heat (convection, conduction, and radiation) laws must be determined. The indoor air model considered consists of three sub-models able to precisely describe its dynamic behavior: relative humidity, indoor air temperature, and CO_2 concentration models. More information related to this simulator, such as the involved equations, its structure, and preliminary evaluations can be found in [35].

The room simulator is able to estimate the PMV index by using the values provided by sensors. As the selected room is devoted to typical office activities, the mean radiant temperature has been obtained from six plane radiant temperatures located in six opposite directions in relation to a seated person. A typical clothing insulation value of 0.5 *clo* (1 $clo = 0.155\ \mathrm{m^2\ {}^{o}C/W}$) (simulations conducted in the summer period) and a metabolic rate of 1.0 *met* (1 $met = 58.15\ \mathrm{W/m^2}$) was chosen.

Consequently, thermal comfort can be controlled by means of the PMV index. The indoor air temperature (t_a) can be indirectly controlled by regulating the fan-coil speed (V_{Fan}). Certain disturbances, such as solar radiation (I_{dr}, I_{df}, and I_{rf}), outdoor air temperature (T_{out}), relative humidity (RH), and people inside the room (N_p), are taken into consideration since they have a substantial influence on the control process.

2.4. Linear Model and Person Profile

Figure 6 shows both the desired PMV in a day and the average occupancy timetable of the laboratory. Thus, from this figure, it can be concluded that the laboratory remains occupied from 8:30 a.m. to 6:45 p.m., which can be considered the working hours. Specifically, people arrive at the lab in the morning. A total of eight people arrive by 9:30 a.m. At 10:30 a.m., four people leave the laboratory to have a break for half an hour. During the afternoon, at 2:30 p.m., six people leave to have lunch and the remaining two depart at 6:45 p.m. The blue solid line in Figure 6 represents the desired reference of the PMV index. As the reader can see, this set-point remains at its optimal value (PMV = 0) during working hours. At other times, the PMV reference is changed to 0.2, which can be defined as a 'ready' state, i.e., the PMV value is kept close to 0 and can be easily changed it to its optimal value. Energy saving increases when nobody is inside the lab.

Ideally, both the PMV and the occupancy repeat every day. As has been pointed out in Section 2.2, the RC can profit from this periodicity to improve system performance.

To check the efficiency that an RC can offer, the performance achieved by three different controllers will be compared. More specifically, a simple proportional–integral (PI) controller, a control system made up of a PI and an RC, and a model-based predictive controller (MPC) will be compared. The MPC is one of the most widespread control methods within academic and industrial fields [49] and it is a well known methodology to maintain thermal comfort since it is widely used by researchers.

All controllers are tuned using a simplified linear model of the laboratory. This linear model is a transfer function in the complex Laplace variable s for the cooling mode, which was obtained by linearizing the non-linear model at a nominal operation point. The transfer function is shown in Equation (3):

$$G(s) = \frac{Y_{PMV}(s)}{U(s)} = \frac{k}{\tau s + 1}; \begin{cases} k = -0.1153 \\ \tau = 474 \end{cases} \tag{3}$$

where in the previous equation, k refers to the static gain in (PMV/(m/s)), whereas (τ) is the time constant in s. The uncertainty of this kind of model does not interfere with closed-loop system requirements; at the same time, the model provides an appropriate performance in simulation.

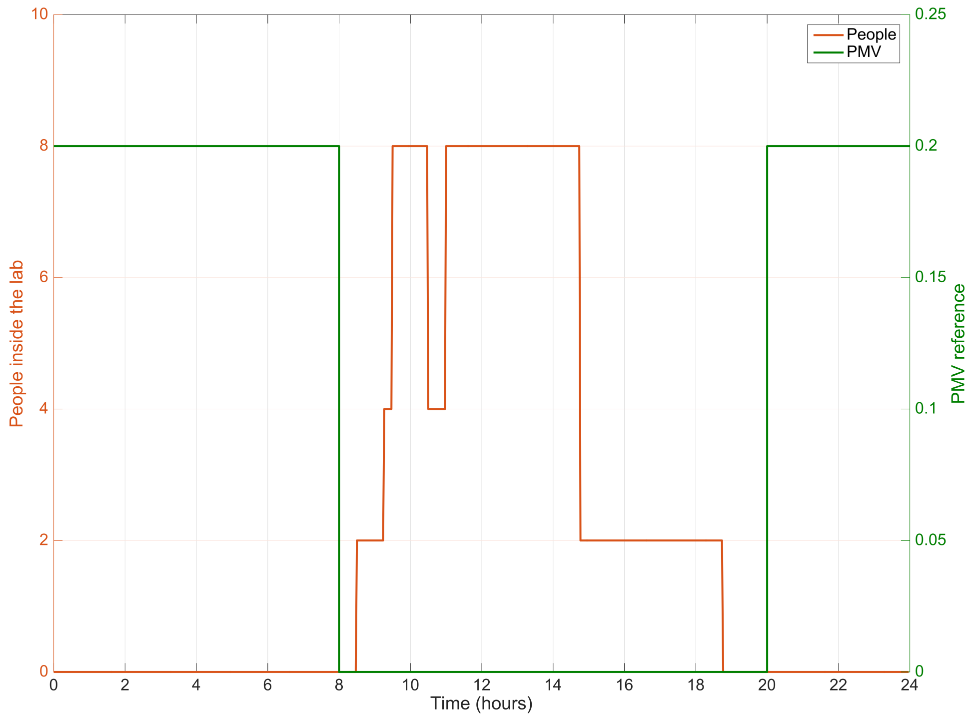

Figure 6. Average person profile and desired PMV profile.

3. Results and Discussion

In this section, several simulation scenarios are carried out in order to check the efficiency of the proposed control system. Firstly, the results obtained in the simulation with the same pattern of people inside the laboratory day after day are shown. Secondly, simulation results using real data from CIESOL building are presented and commented.

3.1. First Simulation Scenario: The Same Person Profile Every Day

Figure 7 shows how the three control systems listed in the previous subsection, that is, the PI, the MPC, and the PI plus the RC, are able to track the PMV reference when the person profile shown in Figure 6 is repeated day after day. It is important to highlight that, the simple PI and the MPC have a behavior which is repeated day after day, whereas the control system which includes the RC controller is able to track the PMV reference almost perfectly, although some small imperfections can be seen due to saturation in the control action. Therefore, the RC profits from the periodicity of person disturbance, while the other control systems without it repeat the error day after day.

3.2. Second Simulation Scenario: Using Real Data from CIESOL Building

In real life, the behavior of people entering and leaving the lab in one day does not have the shape shown in Figure 6, but there are few changes from one day to another. In this subsection, the effects of these little changes, when the three control systems (PI, MPC, and PI+RC) are in charge of the closed-loop performance, are compared using the authentic evolution of the laboratory occupancy during a working week (from Monday to Friday), see Figure 8. The environmental conditions during these days are shown in Figure 9. As the reader can see in the top graph of Figure 9, the solar irradiance (blue solid line) does not have the typical shape of a sunny day due to cloud transients almost over the entire week but especially in the first two days. However, this variable barely influences the thermal conditions of the laboratory due to its northward orientation. On the other hand, the outdoor temperature (red solid line) varies between 10 and 24 °C. From the central graph is possible to highlight that the indoor relative humidity (green solid line) varies in a narrow range whereas the mean radiant temperature (orange solid line) has a range between 19 and 27 °C. Finally, the reader can note that the HVAC was not turned on over the entire week, so the indoor air velocity (bottom graph) has low values.

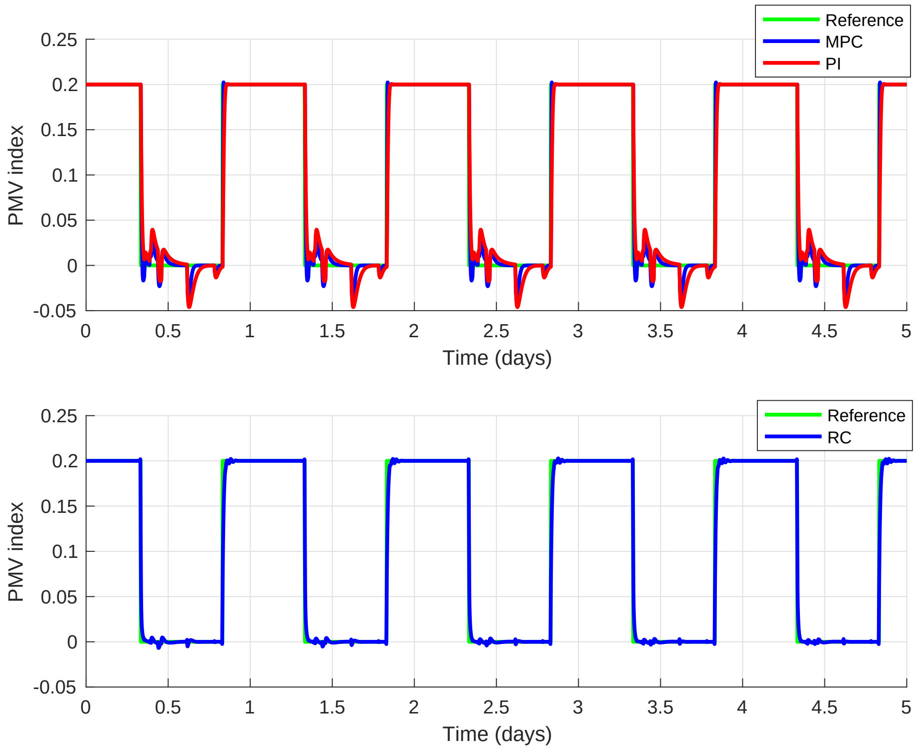

Figure 7. PMV index controlled by three different control strategies: (i) MPC (blue solid line in the upper graph), (ii) PI (red solid line in the upper graph), and (iii) PI+RC (blue solid line in the bottom graph).

The comparison is split into two simulations, in the first one, the control system, which is made up of PI plus RC controllers, is compared with a PI, see Figure 10. The profile shown in Figure 8 is used. The second one shows the efficiency of the control architecture composed of the PI plus the RC versus a more advanced control system: an MPC, see Figure 11. Broadly speaking, the MPC can be defined by the use of the model of the process to predict a future control signal through a prediction horizon, N, while an objective function is minimized. The first step of the predicted control signal is then implemented and the others are rejected, after which the prediction horizon is shifted forward one time sample and the calculations are repeated from the new state. Therefore, it is said that MPC uses a receding horizon strategy [49].

In the first simulation, Figure 10, both control systems are capable of keeping the PMV value close to its desired set-point when no disturbances exist, that is, when the PMV reference is equal to 0.2; however, during working hours, when people come inside and outside of the laboratory and the PMV reference is equal to 0, the control system composed of the PI and the RC can keep the PMV index closer to its set-point more effectively than the simple PI. This better performance is due to the capacity of the RC to anticipate the disturbance caused by people's entering and leaving the lab. However, as the laboratory occupancy profile is not entirely periodic, the RC is slightly worse than the one shown in the entirely periodic case (see the blue solid line in the bottom graph of Figure 7). There is another reason for which RC cannot achieve perfect disturbance rejection: the linear model with which the controllers have been developed, see Equation (3). In this simulation, the proposed control systems are tested through the room simulation tool presented in [35], which makes use of a non-linear model based on energy and mass balances. Therefore, the simulation tool includes dynamics that are not contemplated in the linear model, so the control systems cannot take them into account. In this way, it is possible to obtain a more realistic simulation.

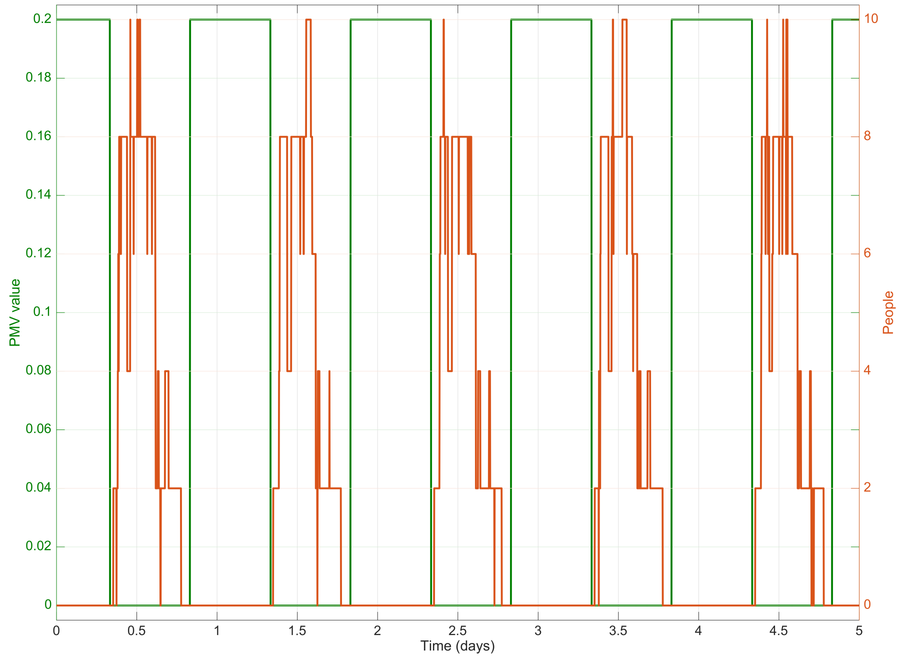

Figure 8. Real people inside the laboratory used during simulation tests (red solid line) and the PMV index set-point (blue solid line).

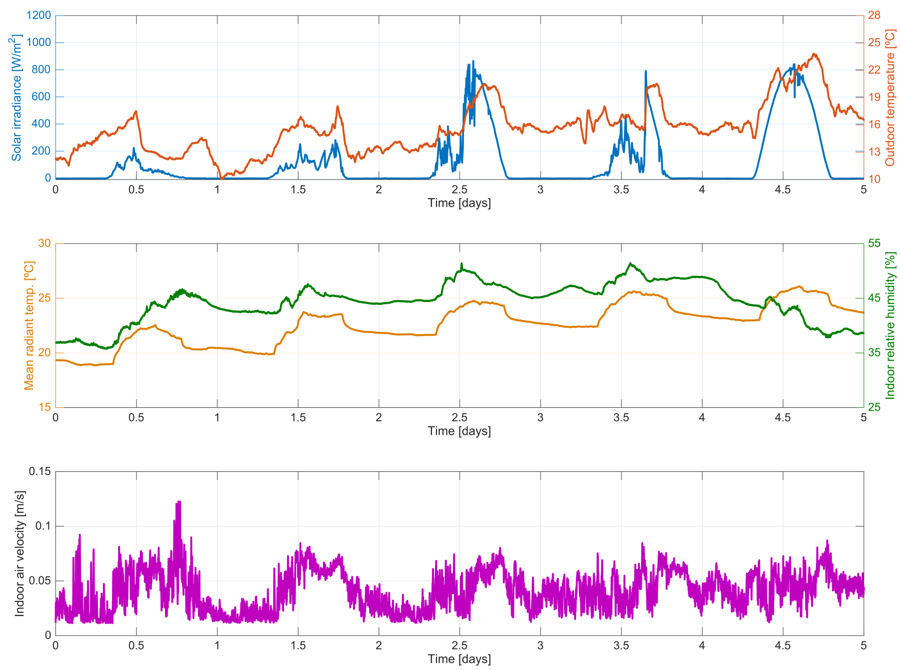

Figure 9. Environmental conditions presented during the simulation tests.

The second test, shown in Figure 11, was performed to compare the control system made up of a PI and an RC versus an MPC. Similar to the previous simulation, the real profile shown in Figure 8 was used. In this case, the MPC outperforms the single PI tested in the previous simulation, see Figure 10, since it is able to more efficiently consider the undesirable effects on thermal comfort caused by people's entering and leaving. However, the PI plus RC control approach outperforms the MPC, even though the MPC is a more advanced control architecture that requires more computational resources.

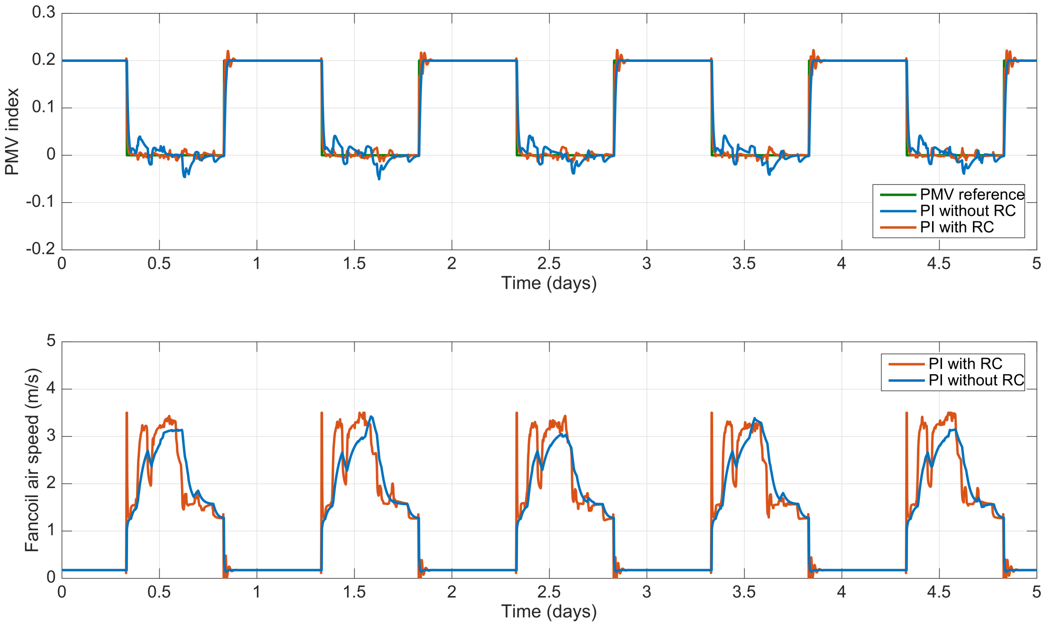

Figure 10. PMV index controlled by two different control strategies: (i) PI (blue solid line in the both graphs) and (ii) PI+RC (red solid line in both graphs). **Upper graph**: PMV index value. **Bottom graph**: control signal, i.e. the fan-coil air speed value.

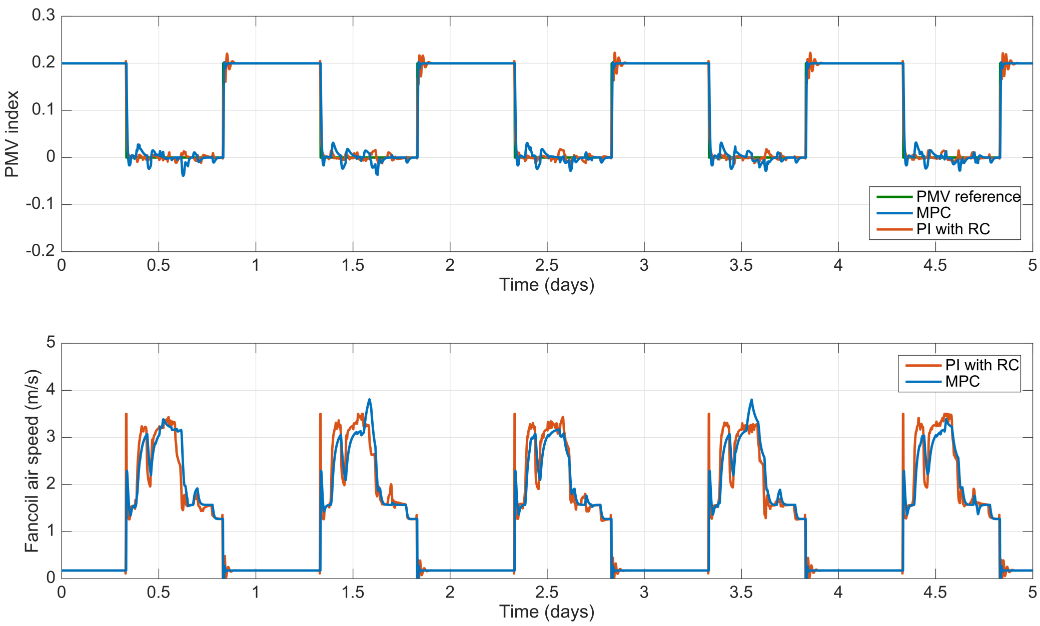

Figure 11. PMV index controlled by two different control strategies: (i) MPC (blue solid line in the both graphs) and (ii) PI+RC (red solid line in both graphs). **Upper graph**: PMV index value. **Bottom graph**: control signal, i.e. the fancoil air speed value.

It is worth mentioning that, if the number of people inside the laboratory or dwelling is larger, the improvement obtained with the RC will increase. Thus, in considerably large dwellings such as hospitals, offices, and shopping centers, where there might be hundreds or even thousands of people occupying the building and it is possible to perform predictions in relation to the people inside the dwelling, the obtained improvement when the RC is added to the control system is larger. The person profile used to train the RC should also be taken into account. The closer a training person profile is to reality, the better the results will be.

4. Conclusions

The development of control systems to reach and maintain people's thermal comfort is a research topic to which governments and private companies are paying attention, since productivity is linked to it. In many works that can be found in the literature, several disturbances, such as weather conditions, outdoor temperature, solar irradiation, and so on, are taken into account since they can influence people's thermal comfort. However, the main weakness of these works is that they do not take into account a person's influence on his/her own thermal comfort since the body itself is one of the main sources of disturbance in comfort control systems. In addition, the number of people within a given building is usually constant; such periodicity can improve the controller performance. RC helps to achieve this end. In this work, the basic concepts of RC and its application to the comfort control of a real room are addressed.

4.1. Summary of the Results

The efficiency of the proposed control scheme has been checked using a simulation tool that uses a non-linear model in order to obtain more realistic results. The control system, which is made up of a PI and an RC, has been compared with a single PI controller and with a more advanced one, an MPC. In both cases, the control system that includes the RC offers better performance, especially if the number of people is constant. In the test bed model presented in this work, the case of a regular laboratory with a capacity of eight people was considered. Due to the small variations in person profile, it is concluded that a reduced number of people may affect system performance. However, the efficiency improvement offered by the RC would be larger in cases of larger offices or buildings due to the increment in the amount of people. It has been demonstrated that the proposed RC is able to learn from periodic behavior, that is, people's input/output patterns, but it is not able to learn from non-periodic behavior, so it may compromise the performance of a closed loop system. To solve this issue, filter design is a key point in developing such control architectures.

4.2. Future Works

Future works will aim to validate the simulation results with experiments. For this aim, the proposed controller must be implemented in the Supervisory Control And Data Acquisition (SCADA) system of the CIESOL building. In addition, an estimator, such as a Kalman filter, will be designed to predict the degree to which people enter and leave the lab.

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Abbreviations

$E(z)$	Error signal $(-)$
$G_c(z)$	Inner controller $(-)$
$G_p(z)$	Plant $(-)$
$G_x(z)$	Stabilizing controller $(-)$
$H(z)$	Null-phase low-pass filter $(-)$
I_{cl}	Basic clothing insulation $((\mathrm{m}^2\ \mathrm{K})/\mathrm{W})$
I_{df}	Diffuse solar irradiance $(\mathrm{W}/\mathrm{m}^2)$
I_{dr}	Direct solar irradiance $(\mathrm{W}/\mathrm{m}^2)$
I_{rf}	Reflected solar irradiance $(\mathrm{W}/\mathrm{m}^2)$
k	Static gain PMV/(m/s)
k_r	Tuning parameter to define the settling time $(-)$
M	Metabolic rate of a person $(\mathrm{W}/\mathrm{m}^2)$
N_p	Number of people in the room $(-)$
$R(z)$	Reference signal $(-)$
RH	Relative humidity (%)
t_a	Indoor air temperature (°C)
t_r	Mean radiant temperature (°C)
T_{out}	Outdoor air temperature (°C)
V_{Fan}	Fan-coil speed (m/s)
v_{ar}	Relative air velocity (m/s)
$W(z)$	Delay function $(-)$
τ	Time constant (s)
HVAC	Heating, Ventilation, and Air Conditioning
LTD	Linear Time-Dependent
LTI	Linear Time-Invariant
MPC	Model-based Predictive Control
NZEB	Nearly Zero-Energy Building
PI	Proportional–Integral
PMV	Predicted Mean Vote
PPD	Predicted Percentage Dissatisfied
RC	Repetitive control
SCADA	Supervisory Control and Data Acquisition

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